Recent Advances in the Field of Trade Theory and Policy Analysis Using Micro-Level Data

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Content

a) Classical regression model

b) Introduction to panel data analysis

a) Classical regression model

- Linear prediction
- Ordinary least squares (OLS) estimator
- Interpretation of coefficients
- Finite-sample properties of the OLS estimator
- Asymptotic properties of the OLS estimator
- Goodness of fit
- Hypothesis testing
- Example

Linear prediction

1. Starting from an economic model and/or an economic intuition, the purpose of regression is to test a theory and/or to estimate a relationship

2. Regression analysis studies the conditional prediction of a dependent (or endogenous) variable y given a vector of regressors (or predictors or covariates) $\boldsymbol{x}$, $E[y|\boldsymbol{x}]$

3. The classical regression model is:
   - A stochastic model: $y = E[y|\boldsymbol{x}] + \varepsilon$, where ε is an error (or disturbance) term
   - A parametric model: $E[y|x] = g(\boldsymbol{x}, \beta)$, where $g(\cdot)$ is a specified function and β a vector of parameters to be estimated
   - A linear model in parameters: $g(\cdot)$ is a linear function, so: $E[y|\boldsymbol{x}] = \boldsymbol{x}'\beta$

Ordinary least squares (OLS) estimator

- With a sample of N observations ($i = 1, \ldots, N$) on y and $\boldsymbol{x}$, the linear regression model is:
$$y_i = x'_i\beta + \varepsilon_i$$
where x_i is a $K \times 1$ regression vector and β is a $K \times 1$ parameter vector (the first element of x_i is a 1 for all i)
- In matrix notation, this is written as $y = X\beta + \varepsilon$

- OLS estimator of β minimizes the sum of squared errors:
$$\sum_{i=1}^{N} \varepsilon_i{}^2 = \varepsilon'\varepsilon = (y - X\beta)'(y - X\beta)$$
which (provided that X is of full column rank K) yields:
$$\hat{\beta}_{OLS} = (X'X)^{-1}X'y = \left(\sum_i x_i x'_i\right)^{-1}\left(\sum_i x_i y_i\right)$$

- This is the best linear predictor of y given $\boldsymbol{x}$ if a squared loss error function $L(e) = e^2$ is used (where $e \equiv y - \hat{y}$ is the prediction error)

Interpretation of coefficients

- Economists are generally interested in marginal effects and elasticities

- Consider the model:

$$y = \beta x + \varepsilon$$

- $\beta = \frac{\partial y}{\partial x}$ gives the marginal effect of x on y

- If there is a dummy variable D, the model is:

$$y = \beta x + \delta D + \varepsilon$$

- $\delta = \frac{\partial y}{\partial D}$ gives the difference in y between the observations for which $D = 1$ and the observations for which $D = 0$
  - Example: if y is firm size and $D = 1$ if the firm exports (and zero otherwise), the estimated coefficient on D is the difference in size between exporters and non-exporters

Interpretation of coefficients (ct'd)

- Often, the baseline model is not a linear one, but is based on exponential mean:

$$y = \exp(\beta x)\varepsilon$$

- This implies a log-linear model of the form:

$$\ln(\mathrm{y}) = \beta x + \ln(\varepsilon)$$

  - $100 * \beta$ is the semi-elasticity of y with respect to x (percentage change in y following a marginal change in x)

- If the log-linear model contains a dummy variable:

$$\ln(\mathrm{y}) = \beta x + \delta D + \ln(\varepsilon)$$

  - The percentage change (p) in y from switching on the dummy is equal to $\exp(\delta) - 1$
  - You can do better and estimate $\hat{p} = \frac{\exp[\hat{\delta}]}{\exp[\frac{1}{2}var(\hat{\delta})]} - 1$, which is consistent and (almost) unbiased

Interpretation of coefficients (ct'd)

- In many applications, the estimated equation is log-log:

$$\ln(y) = \beta \ln(x) + \varepsilon$$

- β is the elasticity of y with respect to x (percentage change in y following a unit percentage increase in x

- Notice that dummies enter linearly in a log-log model, so their interpretation is the one given in the previous slide